Feedback-Based Parameterized Strategies for Improving Performance of Video Surveillance Understanding Frameworks

Nuria Sánchez(✉), Noa García, and José Manuel Menéndez

Grupo de Aplicación de Telecomunicaciones Visuales. ETSI. Telecomunicación, Universidad Politécnica de Madrid. Av Complutense, 30. Madrid – 28040, Spain
{nsa,ngd,jmm}@gatv.ssr.upm.es

Abstract. One of the most ambitious objectives for the Computer Vision research community is to achieve for machines similar capacities to the human's visual and cognitive system, and thus provide a trustworthy description of what is happening in the scene under surveillance. Most of hierarchic and intelligent video-based understanding frameworks proposed so far allow the development of systems with necessary perception, interpretation and learning capabilities to extract knowledge from a broad set of scenarios, having in common the one-way sequential structure of the functional processing units that compose the system. However, only in a limited number of works, once visual evidence is achieved, feedback is provided within the system to improve system's performance in any sense. With this motivation, a methodology for introducing feedback in perceptual systems is proposed. Experimental results demonstrate how different parameterized strategies let the system overcome limitations mainly due to sudden changes in the environmental conditions.

Keywords: Feedback · Scene understanding · Visual interpretation · Knowledge representation · Framework

1 Introduction

One of the most ambitious objectives for the computer vision and pattern recognition research community is to achieve for machines similar capacities to the human's visual and cognitive system, thus, allowing them to understand automatically what is happening in the scene. In the past years, several approaches for the automatic analysis, recognition and description of human-related behaviours have been proposed. As a result, a number of generic integrative frameworks for scenario understanding can be found in the literature.

In a typical Intelligent Transportation Systems scenario [1], where humans and/or vehicles are the usual target objects whose behaviours are analysed, effective and real-time sensor analysis has shown to be a key factor for establishing a reliable monitoring infrastructure [2]. In addition, intelligent capabilities have been proven

A.L.C. Bazzan and K. Pichara (Eds.): IBERAMIA 2014, LNAI 8864, pp. 509–520, 2014.
DOI: 10.1007/978-3-319-12027-0_41

necessary to let these systems reach their full potential [3]. Frameworks like the one proposed in [4] set the basis for developing systems with the necessary perception, interpretation and learning capabilities to understand what is happening in the scene under surveillance. However, there is a need for improving automated surveillance systems' performance, as the environments become more loosely controlled.

Accomplishing so ambitious task requires the incorporation in this kind of understanding frameworks of a feedback control module, like the one proposed in this paper, able to monitor the information processed at different levels of abstraction, control the interactions among independent processing modules and launch at each moment the most suitable feedback strategy so that detection and classification results can be improved.

Experiments will demonstrate, from a practical point of view, the flexibility and effectiveness of the proposed feedback-based parameterized strategies in two different video surveillance domains, having set up the basis for the improvement of existing applications that aim to understand human-related scenarios in other environments.

2 Related Work

In recent years, many automated video understanding systems have been proposed for monitoring human and/or vehicles activities in real scenarios [4]. PRISMATICA [2] and the IBM Smart Surveillance System [5] represent some of the most sophisticated video surveillance systems developed to detect relevant situations in complex real environments such as urban traffic or public transport. In these systems, once system goals are defined, information from a set of selected sensors uses to be analysed using state-of-the-art image processing algorithms and stochastic techniques for data analysis. The common goal consists of translating data in a set of low-level features that provide motion information in the scene as well as other visual cues, allowing the detection, classification and tracking of objects of interest. As a result, higher-level spatio-temporal reasoning modules are provided with the necessary knowledge about the objects and their context, which allows the system to make an inference about the activity being carried out and therefore to describe the scene.

All of them have in common the one-way sequential structure of the functional units that compose the system, i.e. only one module uses to be active at any time, and the communication between modules is unidirectional. Only in a limited number of works, once visual evidence is achieved, feedback is provided within the system to exploit the redundancy of processing enabled at different levels of abstraction in order to improve system's performance in any sense [6]. Feedback is usually introduced either to correct an error or to seek for more information that may help the system to resolve any uncertainty [7]. Focusing on Computer Vision-based applications, the possible strategies to be applied range from fine parameter tuning to overcome limitations due to change in the environmental conditions to the selection of a more suitable image processing algorithm according to the requirements of a particular moment [8].

At the same time, feedback strategies uses to be applied only on individual processing stages with the objective to enhance the results of each stage independently of the results obtained in the other [9]. However, from the authors' point of view, the real challenge consists of exploiting expectations derived from high-level analysis to improve the performance of lower levels of analysis in a more autonomous way, contributing thus to the development of more reliable and intelligent systems [10][11].

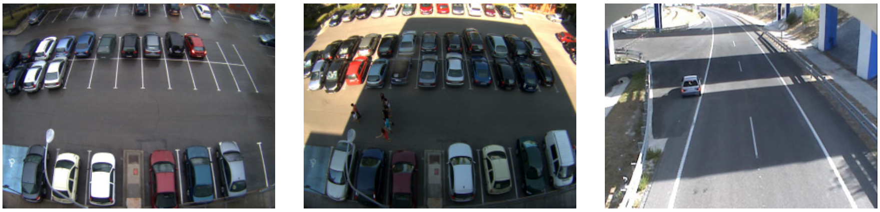
Among these solutions, it can be found, for instance, a self-adaptive real-time tracking system able to judge their own performance and to apply specific repair strategies on other low-level modules when needed; or a video surveillance system able to switch when the people density increases in the scene from an individual to a crowd tracking algorithm is found. In advanced solutions like these, a control module is usually in charge of managing information of completely different nature. In addition, agreement on data structures and reference models is needed to allow bidirectional exchanges of knowledge, so that the output from one module has direct influence on the other module before it finishes processing. But, while it is clear that the concrete implementation of these modules will be always application dependent, a more detailed description of the necessary steps to design a generic feedback control component is needed, so that these video understanding frameworks can be easily adapted to a wide range of domains.

With this motivation, a new methodology for introducing parameterized feedback in perceptual systems is presented in the next Section. The approach assumes that a modular and hierarchical framework for scenario understanding is available, so that different system routines can effectively work at different processing levels A global feedback-based analysis strategy can be thus exploited to combine top-down with bottom-up information in a closed feedback loop. One of the advantages of the proposed solution is that it contributes to simplify the design of this kind of systems considerably since all the required steps are well structured and formalized. It will be demonstrated how thanks to the suitable repair strategy, the performance of baseline systems used for the experiments can be iteratively improved.

3 Challenges of Video Surveillance in Transport Related Scenarios

Many efforts are being made by the scientific community to develop systems able to provide reliable outdoor surveillance at all times, with the capability to cope with changing light and climate conditions, from one minute to the next, and from brightest daylight to darkest night. However, while sensors being deployed already integrate the necessary capabilities to provide clear image quality regardless of weather, lighting or image complexity, processing algorithms which most of video surveillance systems rely on, require of a costly and continuous manual fine tuning in order to be able to adapt to any change in the environmental physical conditions. In order to let the reader understand better the benefits of the integration of feedback control strategies to design more reliable video surveillance systems, before presenting it, two different scenarios will be studied.

First video understanding framework of reference that will serve as baseline system for our experiments is the outdoor vacant parking space detector system proposed by authors in [12] which strongly relies on pyramid of histogram of gradients (PHOG descriptor) extracted from the region of interest to infer whether that region is really occupied or not. Main problems faced by this kind of systems are the low contrast of dark vehicles in shadowed areas in general, most challenging even in a cloudy or rainy day (Figure 1*a*), and the sudden changes in the illumination of a region when a shadow of any object in the surroundings is projected on the parking area (Figure 1*b*). The second video understanding framework of reference will be the system for the automatic detection of traffic incidents in highways proposed by authors in [13] which relies on a background subtraction method to warn about the possibilities of having a new stopped vehicle-related event registered by the system. Figure 1*c* shows the typical illumination challenge the system has to deal with due to shadow projected on the highway when the bridge crossing over is blocking the sun light source. This highway scenario will be also used to demonstrate the flexibility of the proposed approach to handle changes in the logical context and adapt to any new situations that may occur (e.g. after stopping, driver leaves the vehicle).



a *b* *c*

Fig. 1. Different captures from different scenarios under different environmental conditions. Figure *a* corresponds to a parking area in a rainy day in which low contrast images are usually acquired. Figures *b* shows an image from same scenario acquired in a sunny day when shadow cast associated to building in the proximity is projected over the parking area. Figure *c* shows similar problem found in a different scenario (M-12 highway in Spain).

4 Integration of Feedback Control Strategies in the Design of Self-adaptive Perceptual Systems

Feedback can be defined as the process by which a specific processing stage receives information about its success, or otherwise, its bad performance together with the corresponding decision on the most suitable strategy the system needs to launch for its self-improvement [7]. Based on a hypothesis generation-hypothesis verification approach, a general self-adaptive processing scheme to improve classical video understanding frameworks is proposed in this paper as shown in Figure 2.

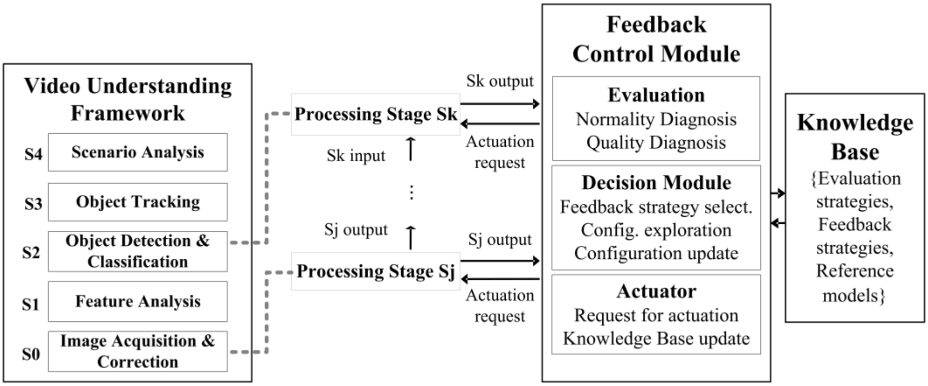


Fig. 2. General self-adaptive processing scheme proposed in this paper to improve performance of classical video understanding frameworks like the ones proposed in [12] and [13]

Unlike other feedback schemes, our approach allows the parameterization of the steps that support the feedback process, ensuring its applicability with independence of the domain, the specific task to be solved and the processing stage(s) which the system will act on. More details are provided in the following sections.

4.1 Knowledge-Based Reference Model, Evaluation and Feedback Strategies

According to authors in [14], a model of system objectives should be the first step in the formulation. Following the schema proposed in Figure 2, the relevant information that is necessary and sufficient for developing a convenient solution needs to be identified and stored in an independent module known as Knowledge Base (KB), contributing thus to favour reusability of developed modules. It is basically a structured database with the *reference model* that lets the Feedback Control Module start operating. Among the information of different nature the most representative is: the list of available algorithms for executing a specific task along with their corresponding identifiers and descriptions, with the input/output variables; configuration parameters with their individual range; and, finally, the contextual data linked to a particular video surveillance scenario integrating information about target objects and key events to be detected, and other logical, spatial or temporal constraints that support the analysis.

For instance, the reference model for the vacant space detector presented in [12] and described above would be composed of the corresponding well-known image-processing algorithms for vehicle modelling in 3D, object detection and target classification. Input/output variables would be image frames, low-level features relying on a set of PHOG descriptors and final target locations respectively. Different configuration parameters could be set as well, from image contrast *c* to the detection thresholds whose values may range from a minimum *th1* to a maximum value *th2*. In the case of the highway incident detection system [13], the reference model would be defined by an adaptive background modelling module which provides information about motion in the image; followed by a shape-based object detection approach in which parameters such as motion detection threshold *th* or shape confidence coefficient *sh* can be adjusted to focus the detection on vehicles and people respectively. Finally, output from a tracking module lets the system supervise at high-level the activity in the scene along the time. Main output parameters are foreground pixels, blob candidates with their respective locations, and the semantic description of events.

Apart from the identification of the particular knowledge-based reference model, the *performance and quality criteria* to be used for the system's self-evaluation needs to be available within the KB prior to the execution of the system. Finally, the list of *feedback strategies* that will be applied in case the result after evaluation may not be good enough, need to be defined as well. Next section introduces the module where all the information available in the KB will be exploited.

4.2 Feedback Control Module

The main contribution of this paper is the generic Feedback Control Module presented in Figure 2, necessary for providing any perceptual system with the necessary self-adaptive capabilities to overcome the typical problems this kind of systems suffer from. This control module is composed of three main sub-modules, which are common to any particular implementation: Evaluation, Decision and Actuation. This basic structure allows the formalization of the general approach to let the system respectively: 1) perform its own diagnosis for self-assessment based on predefined performance or quality criteria; 2) autonomously make a decision on the most appropriate feedback strategy for corrective action or completeness; and, 3) make the corresponding request to a particular module within a processing stage *Si* with $i = 1, 2 \ldots N$, being $N \in Z$ the number of processing stages. The Actuation module is also in charge of keeping the KB continuously updated by tracking changes in the reference model. Specific actions to be carried out by the system during these steps need to be carefully defined. But, in order to ensure the independence of these modules, a good interface is first necessary.

Table 1. Generic communication interface for a self-adaptive processing scheme

Evaluation-related commands
negEval: Negative evaluation after applying performance or quality criteria
posEval: Positive evaluation after applying performance or quality criteria
Decision-related commands
initKB: Initializes the files and defaults necessary to start processing
updateKB: Asks the decision module to make the Knowledge Base up-to-date
getNewStrategy from <feedback_strategies>: New strategy can be still applied
Actuation-related commands
stateUpdate: Confirms the last state in which the processing stage is
selectAlgo from <algorithm_list>: Select algorithm to start processing with
selectParam from <config_param_list>: Select parameter for running algorithm
selectValue from <config_param><type><range_values>: Select value for a parameter
changeAlgo <algorithm_list>: Request for changing the algorithm currently used
changeParam <config_param>: Modify the configuration parameter to be used
changeValue <range_values>: Modify value of the configuration parameter used
infoRequest: Additional queries made by system to retrieve additional information.
responseToQuery: Binary response to additional queries made

For its design, we have taken into account basic semantic information that all modules within the framework should be able to understand in order to increase their knowledge and be able to react after first assessment is made. The most relevant functions used are the ones described in Table 1. Other commands not included allow the communication between the Feedback Control Module and the Knowledge Base.

Evaluation: Normality and Quality Diagnosis Based on Predefined Criteria

For a normality diagnosis, performance evaluation measures allow the Evaluation module automatically measure the 'error' or deviation with respect to the defined value of reference. Quality measures can be also defined as part of the quality diagnosis process inside this module. The performance evaluation and quality measures space is composed of: the list of performance and quality variables, its type and the acceptable response. A space within the KB is reserved for storing this information.

Most of performance measures applied in the literature consist of comparing findings with ground truth. This way, performance variables such as Precision, Recall or Accuracy can be calculated. For instance, in [12] the accuracy is based on the ratio of samples that the system has been able to classify correctly as vehicle among all samples. In the second case [13], authors calculate accuracy comparing the times a particular event ('stopped vehicle') are correctly detected during a video sequence. To let the system further assess on the quality of the results, other measures can be defined. As an example, local contrast or cast shadow probability could be computed for a particular zone within the parking area in [12]; while a shape confidence coefficient could be calculated at each iteration of the tracking module in [13].

Decision and Actuation: From Selection to Validation of Feedback Strategies

One of the most relevant contributions of the present work is the parameterization of the multiple feedback strategies that can be launched to improve the accuracy of this kind of systems. Following the approach in [15], two kinds of feedback strategies are considered: a *repair-oriented feedback* and a *focus-oriented feedback*. The first aims to eliminate errors due to the inconsistency of the new findings in level *Sj* and the knowledge of level *Sk*. The second aims to refine or increment the existing information at any abstraction level. A procedure for managing the interaction between such strategies is then required. Using as input the system evaluation response, a rule-based decision module is proposed as an appropriate solution to achieve this objective. Finally, an actuator is in charge of performing the corresponding decisions and assessing on the suitability of the feedback strategy followed.

First consideration as part of repair-oriented feedback strategies is that decision on the algorithm to be executed at any new iteration needs to be made. The algorithm does not need to be necessarily the same. Additionally, in case of the same algorithm is applied, an adjustment of the initial configuration parameters may be needed. However, sometimes, lack of detail at low level avoids the system being able to detect an object or event with high probability. Focus-oriented feedback strategies would be more suitable in this case to enhance the knowledge about the scenario the system has. Table 2 summarizes the different feedback strategies that would improve the accuracy of systems presented in [12] and [13], altogether with the conditions that must be met to launch the process.

Table 2. List of possible feedback strategies for the scenarios described in Section 3. Corresponding processing stages are identified by *Si* label following the representation in Fig 2. Activity within the Evaluation (E), Decision (D) and Actuator (A) is also identified.

	Outdoor vacant parking space detector system [12]	**System for the automatic detection of incidents in highways [13]**
Repair-oriented feedback strategies	**E >** Accuracy of vehicle detector (S2) below expected. Compute cast shadow probability in S0 to confirm illumination transition in the parking zone. **D >** If transition confirmed, ask S0 to increase image contrast locally. **A >** Actuate on processing stage S0 and continue (S1-S2) **E >** Check if accuracy is improved.	**E >** Accuracy of event detector (S4) below expected. Compute cast shadow probability in S0 to confirm illumination transition in the highway area. **D >** If transition confirmed, ask S1 to adjust motion detection threshold **A >** Actuate on S1 and continue **E >** Check if accuracy is improved.
Focus-oriented feedback strategies	**E >** Accuracy of vehicle detector (S2) below expected but no illumination transition confirmed by S0. **D >** Ask feature analysis module (S1) to change feature extraction strategy (local edge enhancement before PHOG **A >** Actuate on processing stage S1 and continue (S2) **E >** Check if accuracy is improved.	**E >** After stop vehicle has been detected, S4 fails to describe event linked to new object detected by S2. **D >** Ask tracking module S3 to compute shape confidence coefficient and ask S2 launch people detector **A >** Actuate on processing stages S3 and S2 and continue **E >** Check if a person is now detected. High-level description achieved (S4)

5 Experimental Results

In this section, experiments carried out to demonstrate the applicability of the proposed approach on different types of computer vision scenarios and methodologies are described. The objective behind the integration of feedback approaches is to let systems like the proposed in [12] and [13] efficiently tackle problems linked to challenges already identified in Section 3 in an autonomous way, i.e. the impossibility for the system to keep on detecting correctly vehicles when the illumination conditions suddenly change; and the lack of information that can be extracted from the region of interest in the case of low contrast images. Different video sequences corresponding to different scenarios were acquired using an AXIS IP camera: 'Parking B_191112' corresponds to a rainy day and 'Parking B_020713' to sunny day in the same parking area ([12] reported errors in the event of sudden illumination transition and due to dark vehicles on shadowed areas); 'Highway_M12_270711' to sunny day ([13] reported difficulties to detect stopped vehicle during illumination transition, and to detect person leaving the car). Then, details of specific routines implemented within the Feedback Control Module are given below. Information already provided in previous sections may be omitted in order to avoid repetitions.

We will focus first on the outdoor vacant space detector system proposed by authors in [12]. In a training stage, a first normality diagnosis based on differences between vehicle detection results got for frame *f* and ground truth are computed, so that the system is able to assess whether the current detection results in some zones of the parking area are not satisfactory and if, therefore, the accuracy of the system could be likely improved. A quality diagnosis is then performed by the Evaluation module. In particular, a shadow detector module within the image acquisition stage is asked to confirm whether a sudden transition from occlusion shadow to direct lighting up is happening or not. In the event of sudden illumination transition, once the evaluation is carried out, the Decision module selects the most suitable feedback strategy among all available in the Knowledge Base, in particular a repair-oriented strategy recommends increasing image contrast locally. A diagram showing the complete information flow is presented in Figure 3.

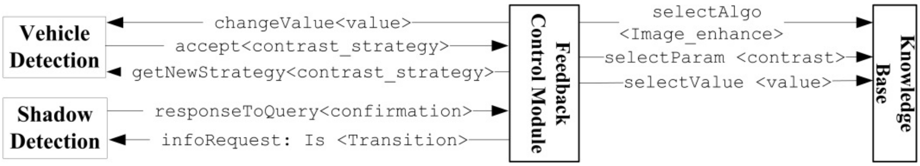


Fig. 3. Proposed repair-oriented feedback strategy for the system in [12]

As introduced in the previous section, objective behind focus-oriented feedback strategies is to let the system decide if the processing stage could provide additional information by executing an additional routine (e.g. multi-resolution analysis on ROI) or if there are elements that can be added to or excluded from the analysis (objects, events not included in the reference models) in order to maximize the information gathered at the same time noise is reduced. Feature analysis performed by system in [12] relies on the analysis of Pyramid Histogram of Oriented Gradients (PHOG) features which basically consists of a set of histograms of orientation gradients computed over an image region that is divided, at each resolution level, into a predetermined number of blocks. One of the problems faced by using these features is the lack of enough information in the presence of low illumination conditions. A focus-oriented feedback strategy is available, which allows the system in this case to have a more robust illumination insensitive image representation of dark vehicles in the image. The algorithm this feedback strategy relies on is the gradient-based pre-processing technique proposed in [16]. Pre-processing of region of interest is shown in Figure 4.

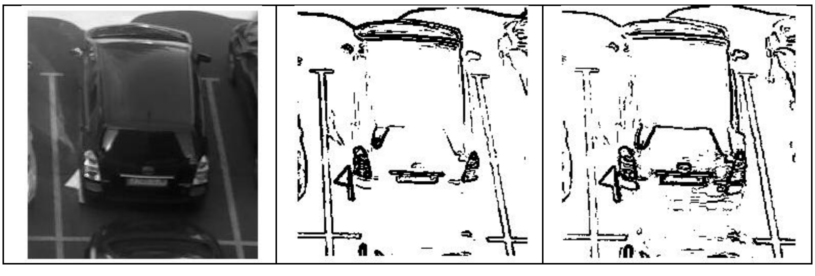


Fig. 4. For a low contrast vehicle sample (left) differences in the gradient image used by the detection stage in the baseline system (middle) and the one used by the same module after applying the focus-oriented feedback strategy (right)

A diagram showing the complete information flow in this case is presented in Figure 5.

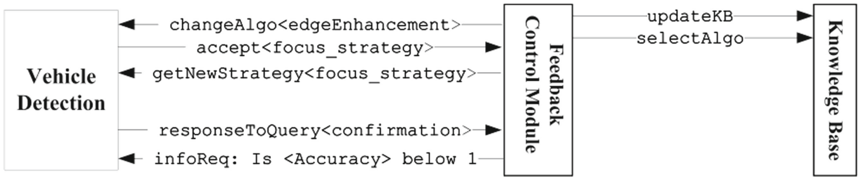


Fig. 5. Proposed focus-oriented feedback strategy for the system in [12]

Figure 6 shows the vehicle detection results before and after the incorporation of suitable feedback strategies in the baseline system [12], being in the last case able to deal with false alarms due to deficiencies or sudden changes in the illumination conditions. The system is optimized for detecting cars so vans may introduce false alarms.

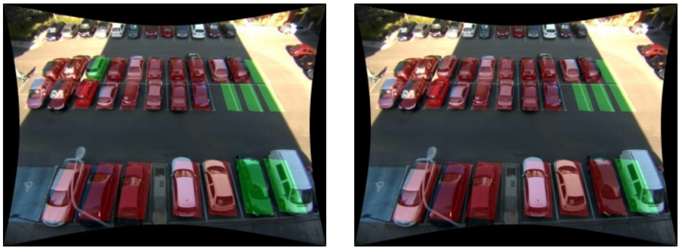


Fig. 6. From left to right, figure shows respectively the improved results in the bottom and top regions after integrating feedback strategies in the baseline system [12]

We will finally show the flexibility of the proposed approach to cope with the requirements of the automatic incident detection system proposed in [13]. In this case, after illumination transition is detected by the Evaluation module, and once assessment on the list of possible feedback strategies is made by the Decision module, the Actuator requests the feature analysis module in charge of analysing motion to rerun the previous frame but with different configuration parameters to those using during the initialization. In this case, relying on the same algorithm (i.e. based on the well-known background subtraction approach) a different threshold is decided to be applied for the affected zone. The reference model available in the KB is updated accordingly with the new configuration parameter. Problems identified for this scenario are completely solved and performance, in terms of accuracy is increased.

Unlike other feedback related approaches which are focused on the improvement of single processing stages, our strategy covers the complete system so that a state-of-art comparison with such approaches is not possible. We will compare instead the results got by two video surveillance systems after applying both a repair-oriented and focus-oriented feedback strategies. Table 3 presents results on selected datasets corresponding to two different scenarios, showing the improvement of the initial system in terms of accuracy as defined before. Not all video sequences may be affected by the same problems. For instance, due to the constant illumination conditions, it may be the case of not registering sudden illumination transition so that the repair-oriented feedback strategy for the parking system proposed in this paper is never launched.

Table 3. Comparison of accuracy rates/final system response when feedback strategies are integrated in the operational workflow of the selected baseline systems [12] and [13]

	Vacant spaces detector [12]		Incident detect. [13]
Video sequence / System tested	Parking B_191112	Parking B_ 020713	Highway_M12 _270711
Baseline system	0.937	0.821	No event detected
Baseline system + repair-oriented feedback strategy	N/A (no illumination transition)	0.873	Stopped vehicle detected
Baseline system + focus-oriented feedback strategy	0.972	0.886	Driver detected on hard shoulder

6 Conclusions and Future Work

Related work in the field serves to justify that, in addition to the emerging communication between two different processing stages which corresponds to a flow of bottom-up information from stage S-1 to its immediately higher level stage S, there is a clear need for a top-down information flow and a continuous updating process that allows the creation of more robust and reliable video surveillance systems. Thanks to the proposed parameterised approach, typical video understanding frameworks can be therefore extended to support the inclusion of the proposed feedback strategies. It has been shown that a well-structured knowledge base needs to be built to identify for each processing stage the reference models, evaluation criteria and the list of feedback analysis strategies to be applied. Once the Knowledge Base is ready, system can start operating in a more reliable and robust manner requiring little adjustment from the developers. The key advantages of the proposed feedback strategy over those integrated in other video understanding frameworks proposed so far are: (1) the global feedback control strategy is independent of the processing stage that triggers it; (2) a control module is in charge of dynamically orchestrating feedback data flow between two independent stages ensuring that information shared can be interpreted by any specific module at a particular abstraction level; (3) thanks to a common communication interface with the feedback control module, feedback not necessarily needs to flow from stage S to processing stage S-1, being possible the interaction between two modules of completely different semantic nature; finally, (4) such a well-structured approach allows the flexible implementation and integration of suitable feedback strategies in existing video understanding frameworks.

Experiments carried out on a baseline video surveillance system show the improvement in performance when different feedback strategies are integrated. In the future, other feedback strategies that exploit high temporal coherence among closer frames in the video sequence will be explored. In addition, additional tests combining multiple feedback strategies will be performed.

References

1. Kumar, P., Ranganath, S., Huang, W., Sengupta, K.: Framework for real-time behavior interpretation from traffic video. IEEE Transactions on Intelligent Transportation Systems **6**(1), 43–53 (2005)
2. Velastin, S.A., Boghossian, B.A., Lo, B.P.L., Sun, J., Vicencio-Silva, M.A.: PRISMATICA: toward ambient intelligence in public transport environments. IEEE Trans. Syst. Man Cybern. Part A **35**(1), 164–182 (2005)
3. Hu, W., Tan, T., Wang, L., Maybank, S.: A survey on visual surveillance of object motion and behaviors. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews **34**(3), 334–352 (2004)
4. Sánchez, N., Menéndez, J.M.: Video Analysis Architecture For Enhancing Pedestrian And Driver Safety In Public Environments. In: 10th International Workshop on Image Analysis for Multimedia Interactive Services (WIAMIS 2009), London (2009)
5. Tian, Y., Brown, L., Hampapur, A., Lu, M., Senior, A., Shu, C.: IBM smart surveillance system (S3): event based video surveillance system with an open and extensible framework. Machine Vision and Applications **19**(5), 315–327 (2008)
6. Oliver, N., Rosario, B., Pentland, A.P.: A Bayesian computer vision system for modelling human interactions. IEEE Transactions on Pattern Analysis and Machine Intelligence **22**(8), 831–843 (2000)
7. Mirmehdi, M., Palmer, P.L., Kittler, J., Dabis, H.: Complex feedback strategies for hypothesis generation and verification. In: BMVC, pp. 1–10 (1996)
8. Hall, D.: Automatic parameter regulation of perceptual systems. Image and Vision Computing **24**(8), 870–881 (2006)
9. Kim, J.: Improved Vehicle Detection Method Using Feedback-AdaBoost Learning. International Journal of Computer Theory & Engineering **5**(1) (2013)
10. Wang, J., Bebis, G., Nicolescu, M., Nicolescu, M., Miller, R.: Improving Target Detection by Coupling It with Tracking. Machine Vision and Applications **20**(4), 205–223 (2009)
11. García, A., Bescós, J.: Video Object Segmentation Based on Feedback Schemes Guided by a Low-Level Scene Ontology. In: Blanc-Talon, J., Bourennane, S., Philips, W., Popescu, D., Scheunders, P. (eds.) ACIVS 2008. LNCS, vol. 5259, pp. 322–333. Springer, Heidelberg (2008)
12. Bravo, C., Sánchez, N., García, N., Menéndez, J.M.: Outdoor Vacant Parking Space Detector for Improving Mobility in Smart Cities. In: Reis, L.P., Correia, L., Cascalho, J. (eds.) EPIA 2013. LNCS, vol. 8154, pp. 30–41. Springer, Heidelberg (2013)
13. Pecharromán, A., Sánchez, N., Torres, J., Menéndez, J.M.: Real-Time Incidents Detection in the Highways of the Future. In: 15th Portuguese Conference on Artificial Intelligence, EPIA 2011, pp. 108–121, Lisbon, Portugal, October 10-13 (2011)
14. Renouf, A., Clouard, R., Revenu, M.: A platform dedicated to knowledge engineering for the development of image processing applications In: AIDSS, pp. 271–276 (2007)
15. Carmona, E.J., Rincón, M., Bachiller, M., Martínez-Cantos, J., Martínez-Tomás, R., Mira, J.: On the effect of feedback in multilevel representation spaces for visual surveillance tasks. Neurocomputing **72**(4), 916–927 (2009)
16. Han, H., Shan, S., Chen, X., Gao, W.: A comparative study on illumination preprocessing in face recognition. Pattern Recognition **46**(6), 1691–1699 (2013)